PREDICTING LOCATIONS FOR URBAN TREE PLANTING

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Steven M. King

PREDICTING LOCATIONS FOR URBAN TREE PLANTING

The purpose of this study was to locate the most suitable blocks to plant trees within Indianapolis, Indiana's Near Eastside Community (NESCO). LiDAR data were utilized, with 1.0 meter average post spacing, captured by the Indiana Statewide Imagery and LiDAR Program from March 13, 2011 to April 30, 2012, to conduct a covertype classification and identify blocks that have low canopies, high impervious surfaces and high surface temperatures. Tree plantings in these blocks can help mitigate the effects of the urban heat island effect. Using 2010 U.S. Census demographic data and the principal component analysis, block groups with high social vulnerability were determined, and tree plantings in these locations could help reduce mortality from extreme heat events. This study also determined high and low priority plantable space in order to emphasize plantable spaces with the potential to shade buildings; this can reduce cooling costs and the urban heat island, and it can maximize the potential of each planted tree.

Daniel P. Johnson Ph.D., Chair

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INTRODUCTION

Urban tree planting is one of the best ways to mitigate the effects of the urban heat island effect (UHIE). Trees are more effective at reducing urban heating if they shade impervious surfaces which are one of the causes of the UHIE (US EPA, 2009). Trees can be even more effective if the impervious surface being shaded is a building that inevitably must be cooled, thereby reducing energy consumption. The most effective and lifesaving use of trees is if they are planted in a space that would shade a building where socially vulnerable (SV) people reside. SV people may lack resources to effectively cool their residences or lack the mobility to move to a safe cool environment. A residence without air conditioning, but shaded by trees, would not be as hot as the same residence in direct sunlight. Unfocused tree planting would not effectively address the challenge of helping vulnerable populations. The purpose of this study is to identify the census blocks that are most suitable for tree planting. The most suitable blocks will be those that contain the most vulnerable people, the most impervious manmade surfaces, and the least tree canopy. In order to support focused tree planting the selected blocks must contain plantable spaces (grass or bare earth) preferably along the south and west sides (135- 270 degrees) of buildings (Donovan, Butry, 2009). Planting trees along the south and west sides of buildings offers the potential to eventually shade that building. Non-profits like Keep Indianapolis Beautiful, Inc. (KIB) would then need to create a method or develop criteria to identify which buildings qualify for tree plantings. Potential criteria include: is the residence occupied, are there plantable spaces that could eventually shade the residence without affecting sewer lines, power lines or other buildings, and is the owner willing to allow trees to be planted?

As city budgets tighten, money for planting trees is reduced. To garner the most benefit from each planted tree, government agencies and non-profits have more recently started creating models of various characteristics of the urban environment and basing decisions on the results of these models (Texas Trees Foundation, 2010). This study starts with a covertype classification of the study area using LiDAR data. This classification yields designations of canopy, impervious surface, and grass or plantable space. Impervious surfaces include buildings, roads, parking lots, sidewalks and driveways.

This classification is broken up into smaller census block areas with individual percentages of canopy, impervious surface and plantable space calculated for each census block. The block level is the smallest-sized unit of census data, but not all census data is available at this level. This scale gives a more accurate and realistic view of the study area. The next larger census grouping, the “block group”, usually consists of approximately 20 blocks. Block groups can have small pockets hidden within them containing the characteristics we may be seeking to mitigate. These characteristics would stand out more clearly at the block level. Using the block level should help to pinpoint areas that would most benefit from having trees planted within them, allowing an efficient, focused, tree planting regime.

The benefits of trees are well established; they provide shade, cooling of the environment, soil stabilization, food and shelter for wildlife, cleaner air, increased oxygen, reduced water runoff, and a positive aesthetic landscape (Tooke, et al., 2009). The negative aspects of trees are rarely mentioned but are equally important. Trees can be hazardous, can also be expensive to plant and maintain, and must eventually be removed, all at great cost to homeowners, businesses, and municipalities. Many trees require yearly intensive clean up after dropping flowers, seeds and leaves. Some tree species do not filter the air but actually emit volatile organic compounds. (Rosenfeld, Romm and Akbari, 1997). Trees can cause allergic reactions in some people. Tree roots can clog drainage tiles or damage sidewalks, driveways, and roads. Falling limbs and trees can be deadly and costly hazards. The arborist or urban forester must choose or recommend the best species for each environment, the species that will have the maximum benefits. They must also choose the ideal locations for the trees. The product of this study can be used as a tool to, firstly, show which blocks would be most suitable to have trees planted within them and secondly, which plantable spaces within each block would provide the most benefit in regard to shading buildings.

This study will utilize physical variables and social variables. The physical variables are those garnered from the environment such as those already mentioned: canopy, impervious surface and plantable space. Surface temperature or average surface temperature by block is another physical variable. High surface temperature is often a result of the presence of large areas of impervious surface and can precisely determine where the urban heat island (UHI) is strongest (US EPA, 2009).

Social variables are those demographic data that can be used to indicate where SV people are located. The locations of these at risk populations can be determined by using specific census demographic data such as: population age 65 and older, population age 5 and under, median income, population below poverty level, and education level attained (Cutter, 2003 and StatSoft, 2011). This data is available at the census block group. A principal component analysis (PCA) was conducted with demographic variables from the block group level and all blocks within a specific block group were given the same social vulnerability rating.

The social variables were then merged with the physical variables by conducting another PCA in order to determine the blocks that would be the most suitable to plant trees in. For the purposes of this study suitable means: serving the vulnerable, mitigating the UHIE, reducing exposed impervious surface, increasing areas of low canopy, utilizing the best plantable spaces, maximizing the efforts of those doing the planting and maximizing the utility of the trees themselves. Of course some of these perceived benefits rely on the expertise of individuals and organizations to utilize the product of this study in conjunction with best practices in order to be effective.

BACKGROUND

Urban Heat Islands

Urban heat islands are defined as relatively higher air temperature near the surface within an urban area as compared to the surrounding rural area. UHI's are at their greatest intensity during the nighttime hours as manmade surfaces slowly release their stored heat. UHI intensity is the measured temperature difference in the urban setting as compared to the surrounding rural countryside (Voogt, 2002).The main causes of UHI are the modifications of the earth's surface by using heat retaining materials (Kaya, 2012). Factors that contribute to the UHI are: prevalence of heat-absorbing, impervious surfaces such as asphalt, concrete, stone, and brick; the comparably smaller percentage of canopy coverage from trees that reduce heat buildup and provide evapotranspiration cooling; and the so-called sky view factors caused by buildings creating narrow canyons that are filled with heat as opposed to larger open spaces that can dissipate heat. The region's weather, location, time of day and season contribute to the presence and intensity of the UHI (Oke, 1982, 1997)

UHI can be broken down into three layers. The surface heat island is just that, the surface temperature. This is most easily measured by remote sensors. The canopy layer extends up from the surface to treetop level and represents the space between buildings; a measure of this layer can give a localized intensity of the UHI. Lastly, the boundary layer heat island can extend upward to 1000m and vary in thickness, usually less at night. This layer makes up the dome of hotter air that extends downwind from the urban area (Kaya, 2012).

Another contributor to the UHI is the anthropomorphic effects of human activity: vehicle emissions, air conditioning usage, and factories all emitting heat into the surroundings. Also, as urbanization and populations increase, the greater the earth's surface is modified, and the negative effects of air and soil pollution create a cumulative effect that increases the intensity of the UHI (Kaya, 2012).

Social Vulnerability

Social vulnerability is a measure of the vulnerability of the population at that location to risks. The deadliest risks are extreme heat events (EHE) or heat waves. UHIE exacerbates the effects of EHE. The locations with highest SV can be determined by using census demographic data. With the higher temperature in the urban environment caused by UHIE, the population is at greater risk to the effects of EHE. Deaths from EHE can be difficult to determine but Abidine, et al. (2007) states that EHEs are the deadliest environmental hazards in North America. By using Cutter's social vulnerability index it is possible to determine the people who are most likely to be affected by such environmental hazards. Additionally, using socioeconomic and demographic data, the locations of the most vulnerable people can be determined and possibly mitigated (Cutter, 2003). The very old (65 and older) and the very young (less than 5), the poor, and under-educated have been determined to be the most vulnerable classes.

LiDAR Data

LiDAR stands for Light Detection and Ranging and is an accepted technique for creating maps with precise surface characteristics. LiDAR is an "active" remote sensing technique that uses light pulses in a similar way that RADAR uses radio waves. Very dense point elevation data sets can be used to create three-dimensional maps of the areas "flown." Point spacing or "post spacing" can be measured in centimeters. Some of the advantages of LiDAR are that it is hyper-accurate, it is not daylight dependent, and many surfaces can be seen "through." Multiple returns from one light pulse can be measured (see Figure 1). This use of returns can be used to measure the height of objects like treetop canopy and the ground elevation beneath it or water surface level and sea floor depth beneath (as long as light can pass through the water). Intensity is a term used with LiDAR data to measure the strength of the reflective quality of the surface that the light is bouncing off of (NOAA, 2012). Returns and intensity were used to create the classification of the study area. One major advantage of using LiDAR data for this study compared with National Agricultural Imagery Program (NAIP) aerial images of the same area is the total absence of shadows. The NAIP images available had 20 percent shading essentially obscuring that portion of the image.

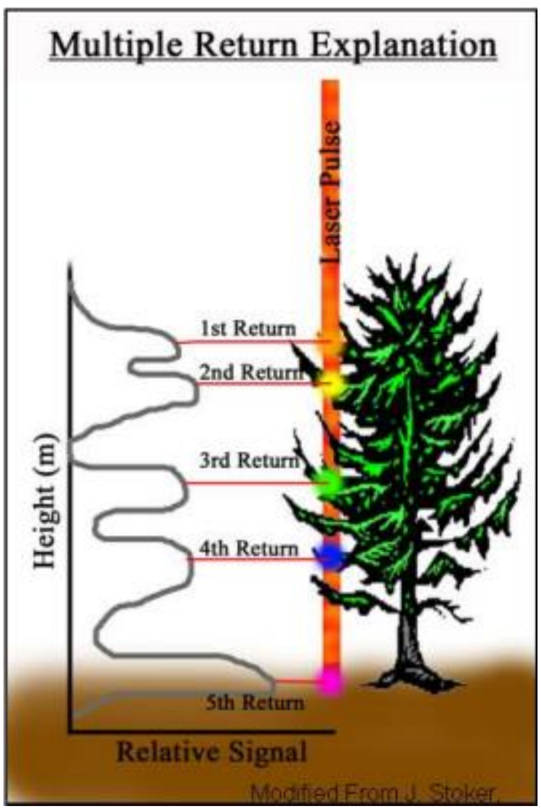

Figure 1: LiDAR Returns: http://www.csc.noaa.gov/digitalcoast/_/pdf/lidar101.pdf

METHODS

Study Area

The Near Eastside Community (NESCO) is located within Indianapolis, Indiana, just east of the central business district and approximately 3 miles west to east and 2 miles north to south (see Figure 2). The neighborhood consists of mostly single-family dwellings built in the very late 19th to mid-20th century. The oldest homes are in the western portion of the neighborhood. The streets are predominantly laid out in a grid pattern of north/south and east/west streets with the houses set close to one another. There are east/west business corridors along Washington St. in the southern part of the study area and along Michigan St. and 10th St (see Figure 3). The Washington St. corridor has more businesses, apartment buildings and parking lots. NESCO also has Pogue's Run creek flowing along a green space that includes multiple parks from the northeast to the southwest, where it goes underground at Michigan St. and continues to downtown Indianapolis. Pleasant Run creek briefly crosses the southeast corner of NESCO. There are also multiple railroad tracks, one going east and west at the very southern edge of the study area, and another running north and south in the center of NESCO. There are also a few large areas of land within NESCO that are industrial factories and school grounds. NESCO consists of 38 census block groups and 671 census blocks.

The ground gently slopes from higher in the east to slightly lower in the west; there are no noticeable hills, and the only small hillocks are along the Pogue's Run and Pleasant Run embankments. The trees within NESCO are typical Midwestern United States trees. The street trees are many varieties of maples, ashes, oaks and elms. Around homes and businesses, more coniferous pines, spruces and cedar are found as well as smaller dogwoods, redbuds, and viburnums. Along railroad tracks, uncleared areas and park understory, the invasive honeysuckle can dominate, but mulberry, hackberry, and osage orange are also found.

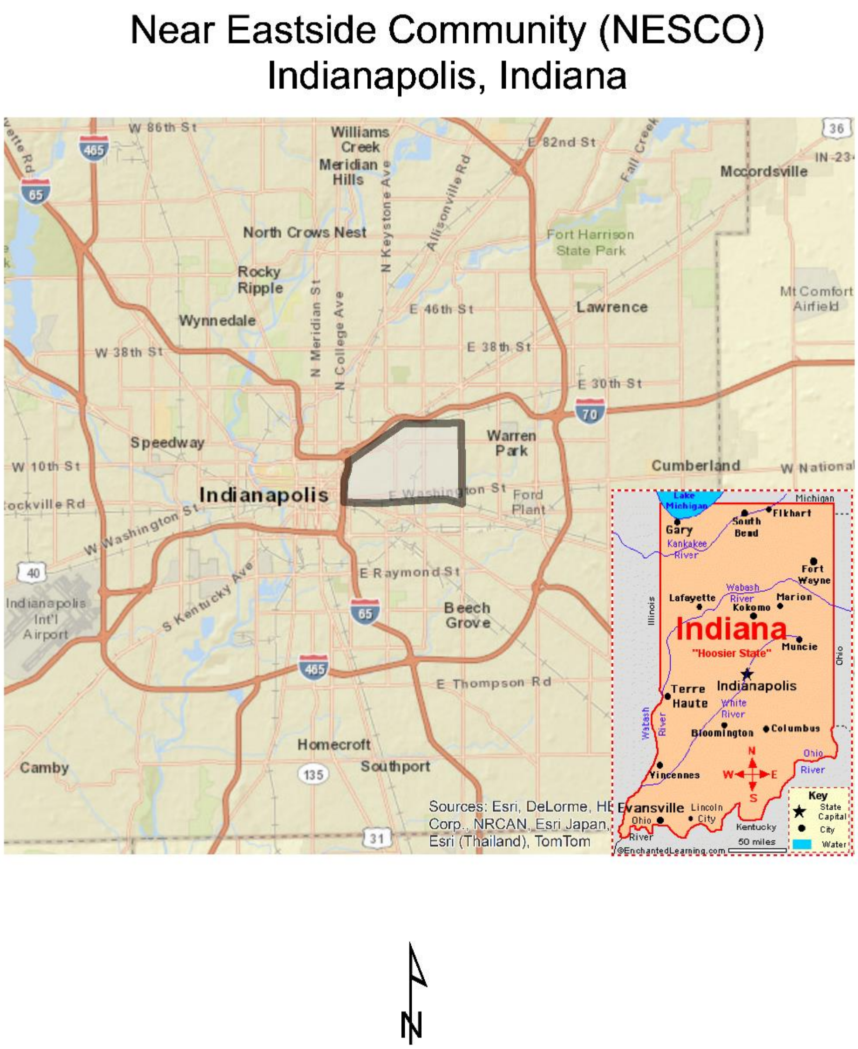

Figure 2: Near Eastside Community (NESCO), Indianapolis, Indiana

Near Eastside Community (NESCO)
Indianapolis, Indiana

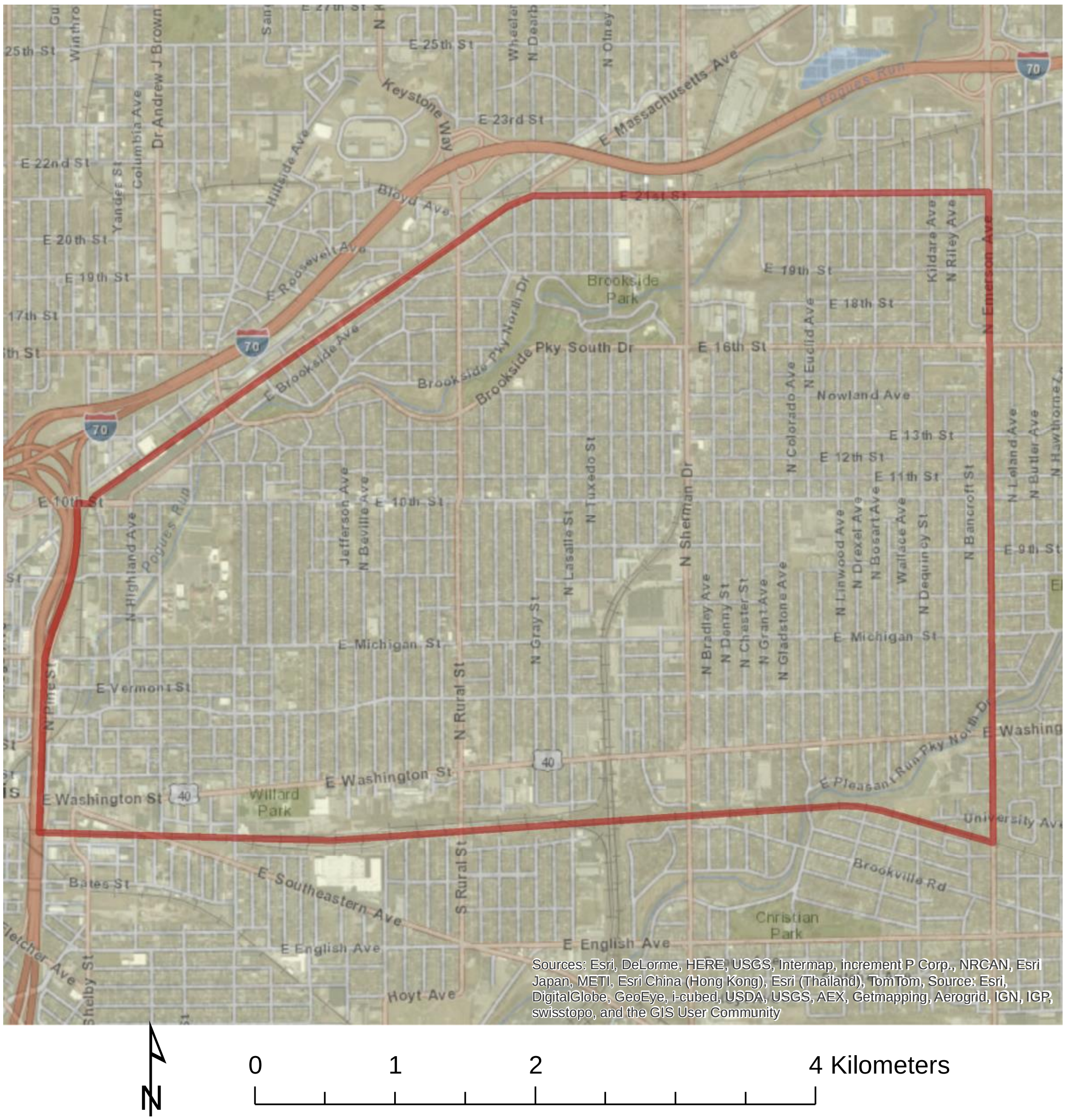

Figure 3: NESCO Streets

LiDAR Classification

LiDAR data for Indiana is available from Open Topography which is linked from the Indiana Map website: http://www.indianamap.org/resources.php. The data was gathered from March 2011 to April 2012, has an average 1 meter post spacing and was used to analyze the NESCO urban canopy. Downloaded LiDAR data must be converted to a LAS Dataset in ArcMap for it to be useful. In order to identify canopy within the LAS dataset, returns must be filtered so only "first of many" and "last of many" are checked (Ye, 2014). The results were then converted to raster. To determine plantable space or grass, intensity was selected and used to isolate grass because it has higher intensity than other surfaces.

The process of converting LiDAR/ LAS datasets into polygon shapefiles and using those shapfiles, some with close to a million polygons each, in Arcmap can be intensive. The computing times for each process when working with such large layers can be 10-20 minutes on an average desktop computer. NESCO consists of only 3-4 percent of Marion County, consequently a larger study area could become a computer resource and time management challenge.

Surface Temperature

Surface temperature was determined by using a Landsat7 ETM+ image of the study area from July 23, 2011 the warmest, most unobscured image available. Landsat images are available from: http://earthexplorer.usgs.gov/. Murayama and Lwin' downloadable model available at: http://giswin.geo.tsukuba.ac.jp/sis/tutorial/koko/SurfaceTemp/Surface Temperature.pdf was used to run the calculations along with Earth Resources Data Analysis System (ERDAS) Imagine software. The model converts the digital number to spectral radiance and spectral radiance to degrees Kelvin. Finally, degrees Kelvin is converted to temperature Celsius (see Figure 4). The results give a land surface temperature at 30m x 30m pixel size of the Landsat image. These results were used to calculate an average surface temperature for each block, from which the warmest areas in NESCO can be determined. These warmest areas are where the UHIE is at its greatest, and likely impervious surfaces are predominant (US EPA, 2011).

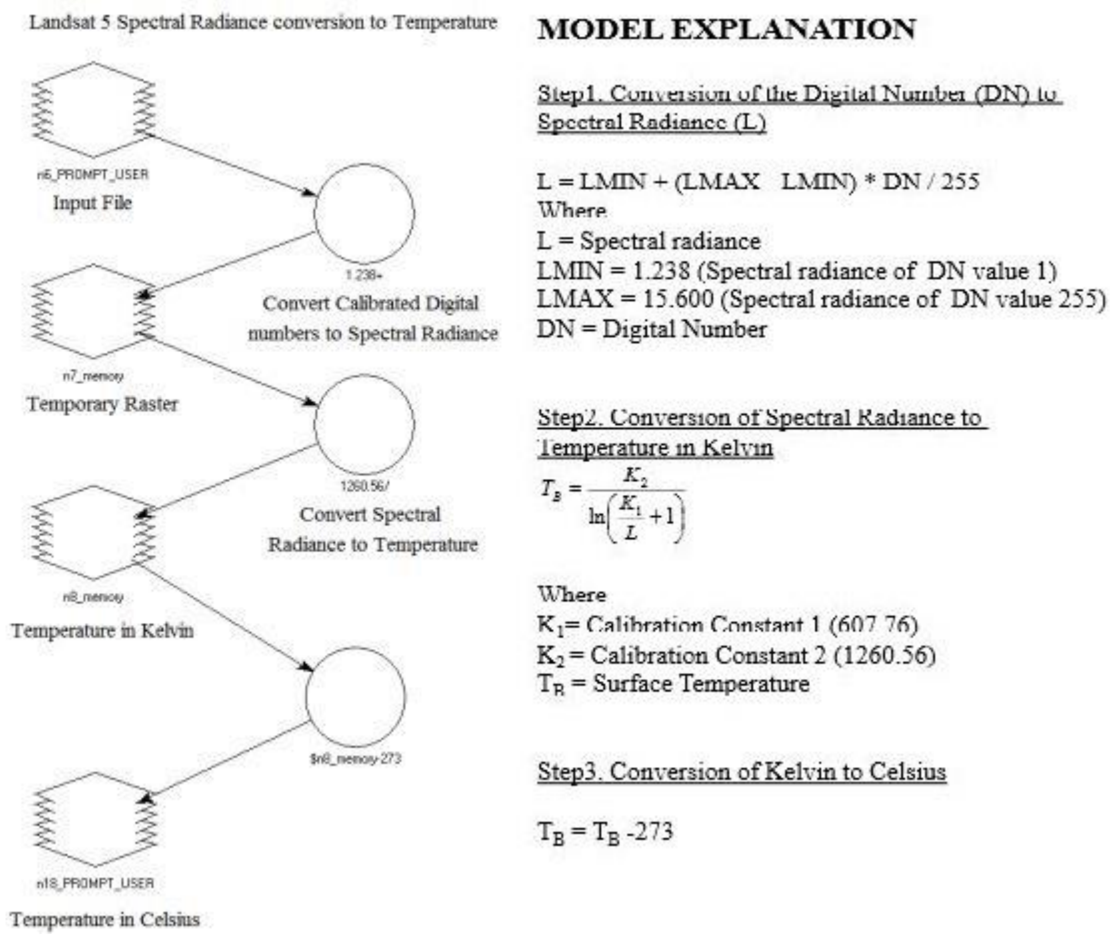

Figure 4: Surface Temperature Model (http://giswin.geo.tsukuba.ac.jp/sis/tutorial/koko/ SurfaceTemp/ SurfaceTemperature.pdf)

Social Vulnerability Data

The relative vulnerability of a population, in this study, block group populations, can be determined by the analysis of specific census demographic data. The most telling and significant variables include age, economics, and education (Armstrong, 2003). Specifically the variables used were: age greater than 65, age less than 5, median income, age 25 or greater without high school diploma, and population below poverty level (Johnson et al., 2009). This data is available from the 2010 United States Census. All demographic data is available only at the census block group level or greater. Therefore, SV was determined at the block group level, and all blocks within a specific block group were given the same SV rating.

Principal Component Analysis

Principal Component Analysis (PCA) is a statistical tool used to analyze data with multiple variables in order to explain how groups of variables account for the most variance and precisely how much of the variance each component represents. It is also a variable reduction tool, the most significant groups of variables can be determined from the results. For the SV PCA, all variables were converted to z scores. The scree plot was used to view PCA results to see component Eigenvalues (StatSoft, 2011). Those components with Eigenvalues greater than one were retained along with their corresponding z scores. The resulting z scores for each block group were added to give a SV score that is relative to all other block groups within the study area. All statistical calculations were done in International Business Machines Corporation (IBM): Statistical Package for the Social Sciences (SPSS). Strength of relationships between variables can be determined in SPSS output pattern and component matrixes.

The same procedure, PCA, was conducted at the block level using the physical variables and the social variables. Block population count was used as a variable in order to increase the likelihood of planting trees in the blocks with the most people. All variables were converted to z scores. Canopy percentage was the sole exception, and it was converted to a negative z score in order to be used to select blocks with low canopy percentage. Again only components with

Eigenvalues greater than one were used, and the component z scores for each block were added together to create a choropleth map resulting in the blocks that would be most and least suitable for tree planting.

RESULTS

LiDAR Classification

Percent area classified as canopy for all of NESCO is 16.95, plantable space is 22.68, and impervious surface is 60.37 (see Figure 5). Percent area of canopy, plantable space, and impervious surface by block as derived from the LiDAR dataset ranged between 0.00 and 54.25, and plantable space was at 0.11 to 80.01, and impervious surface was 3.56 to 100.00 (see Appendix). The wide range of percentages are a result of some block units being very small and consisting of homogenous surfaces of grass (parks) or impervious surfaces (buildings and parking lots).

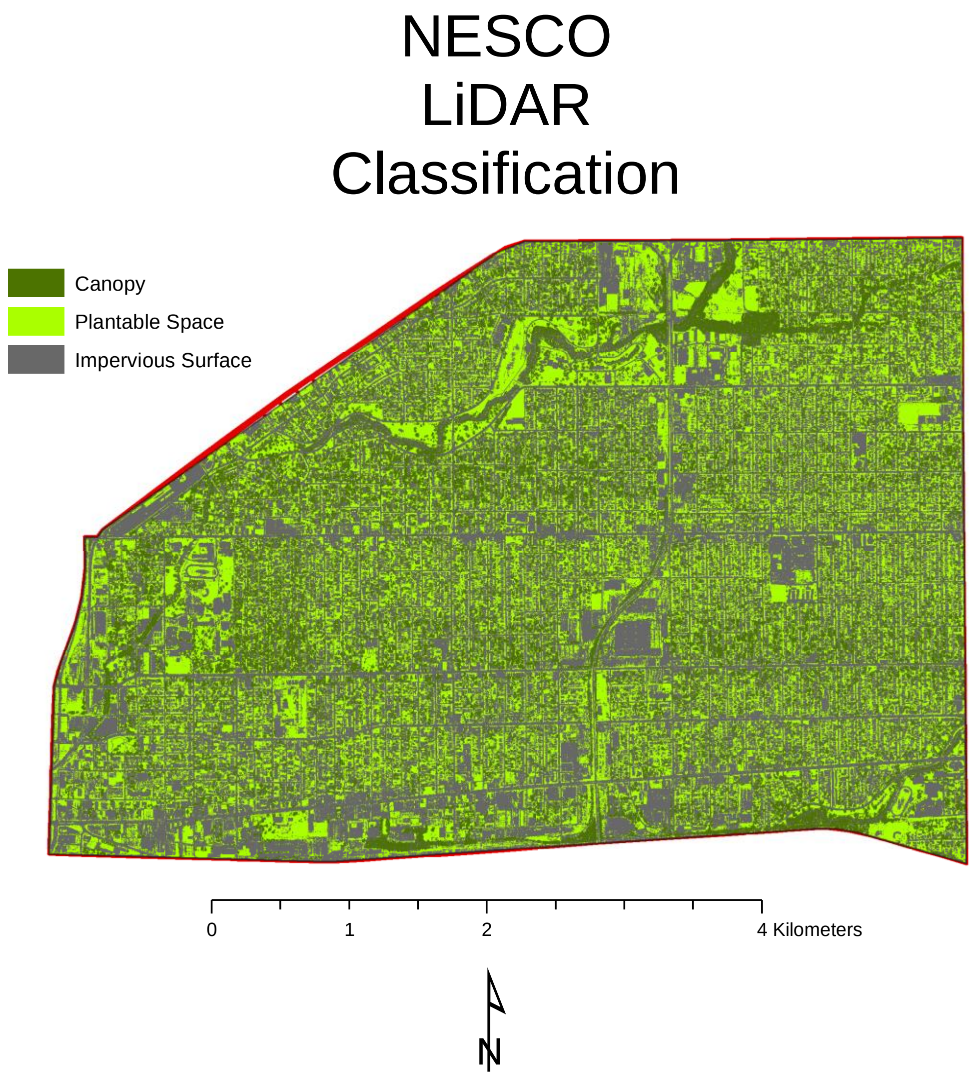

Figure 5: NESCO LiDAR Classification

Figure 6: LiDAR Classification Compared with Google Maps Image (https://maps.google.com/)

Surface Temperature

The results of Murayama and Lwin's ERDAS surface temperature model that utilized a LandSat7 ETM+ image of the study area found that the temperature ranged from 28.0 to 33.5 degrees Celsius (see Figure 7). The results were derived from an intersection of the resulting image and a NESCO block shapefile from which zonal statistics were calculated and used to determine the average temperature for each block.

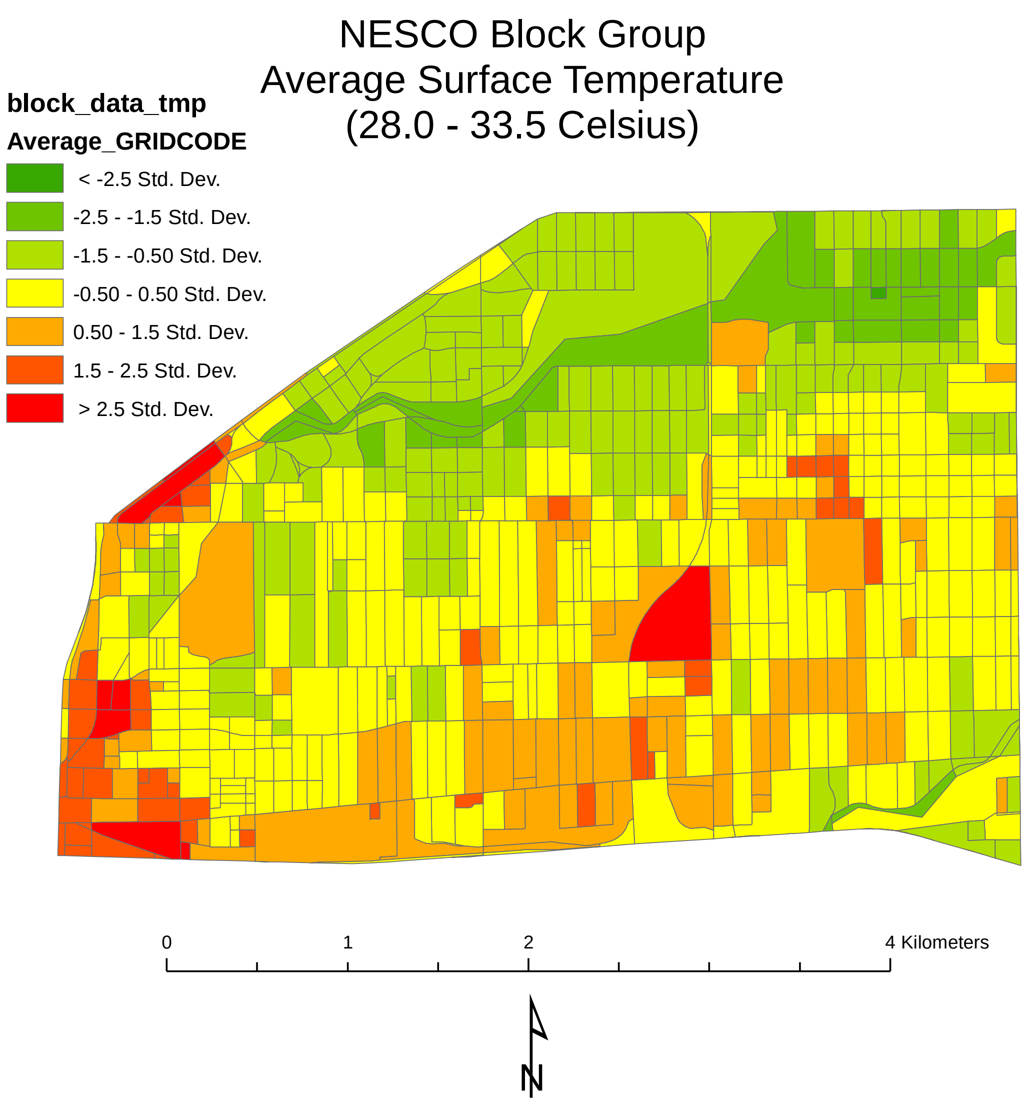

Figure 7: NESCO Surface Temperature by Block

Social Vulnerability PCA Block Group Level

Each variable was displayed in a map in order to visualize a distribution of the data and to see if any trends were present (see Appendix). SPSS was used to run the PCA of the five social variables: age 65 and above, age 5 and under, age 25 and older without high school diploma or GED, individuals under poverty level, and median income. The results showed two components of the PCA were above an Eigenvalue of one (see Figure 8). The first component explained 41.942 percent of the variance, and the second component explained 20.453 percent for a total of 62.395 percent variance explained (see Table 1). Component one showed strong correlation between all variables except age 65 and above. The strong (negative) correlation between median income and individuals under poverty level is expected since median income goes down as the number of people below poverty line increases. Component two consisted of the variable "age 65 and above" acting by itself, independent of the other variables (see Table 3). The resulting individual block group z scores from both components one and two, which were of equal importance, were added together in order to derive the map showing SV within NESCO. The most vulnerable areas of NESCO were generally in the center section of the study area, with less vulnerable areas to the east and west. It should be noted that NESCO as compared to most other portions of Center Township, Indianapolis, is more socially vulnerable than the surrounding areas (see Figure 9) (Rigg 2012).

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.097	41.942	41.942	2.097	41.942	41.942
2	1.023	20.453	62.395	1.023	20.453	62.395
3	.843	16.865	79.260			
4	.776	15.529	94.789			
5	.261	5.211	100.000			

Table 1: Block Group SV PCA Total Variance Explained

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.556
Bartlett's Test of Sphericity	Approx. Chi-Square	34.688
	df	10
	Sig.	.000

Table 2: Block Group SV PCA KMO and Bartlett's Test

Component Matrix[a]

	Component	
	1	2
Zscore: median income	-.850	-.272
Zscore: %pop below poverty	.832	-.018
Zscore: %pop no high school	.602	.097
Zscore: %pop5 down	.535	-.187
Zscore: %pop65up	-.184	.951

Extraction Method: Principal Component Analysis.[a]

a. 2 components extracted.

Table 3: Block Group SV PCA Component Matrix

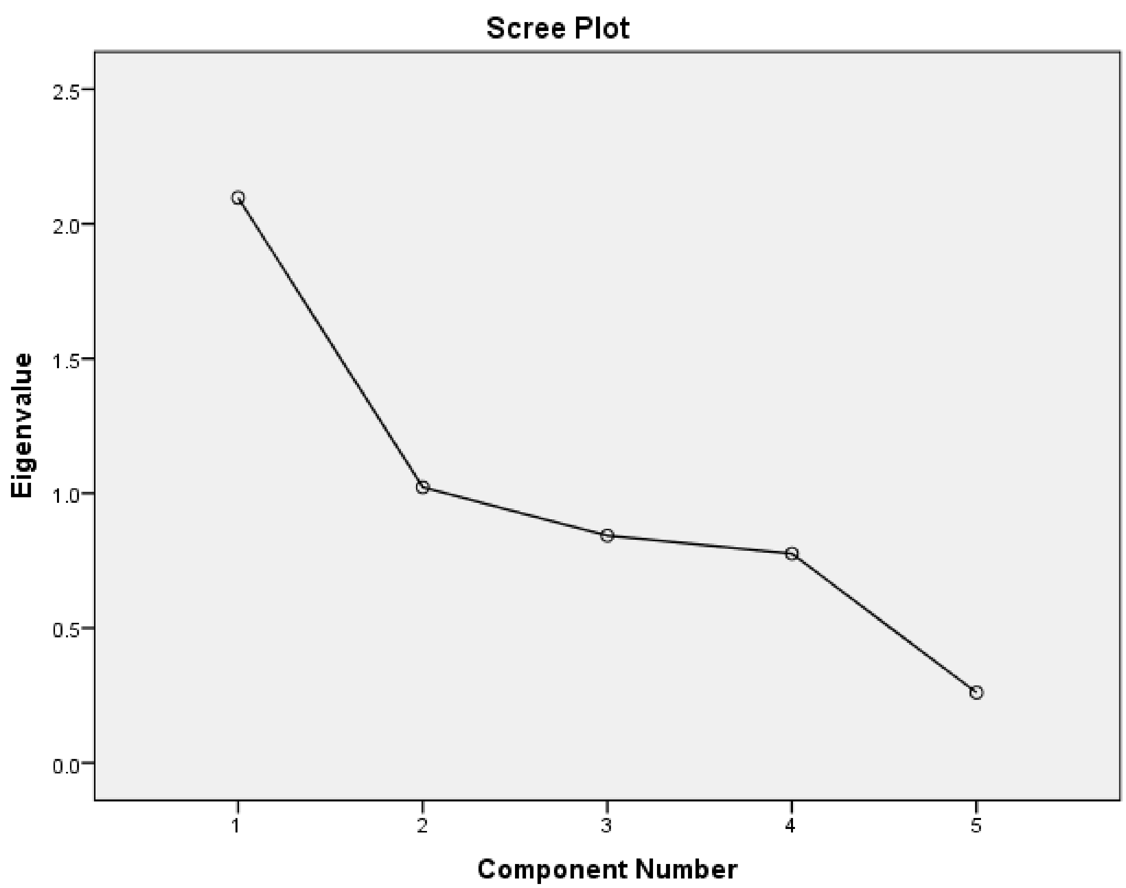

Figure 8: Block Group SV PCA Scree Plot

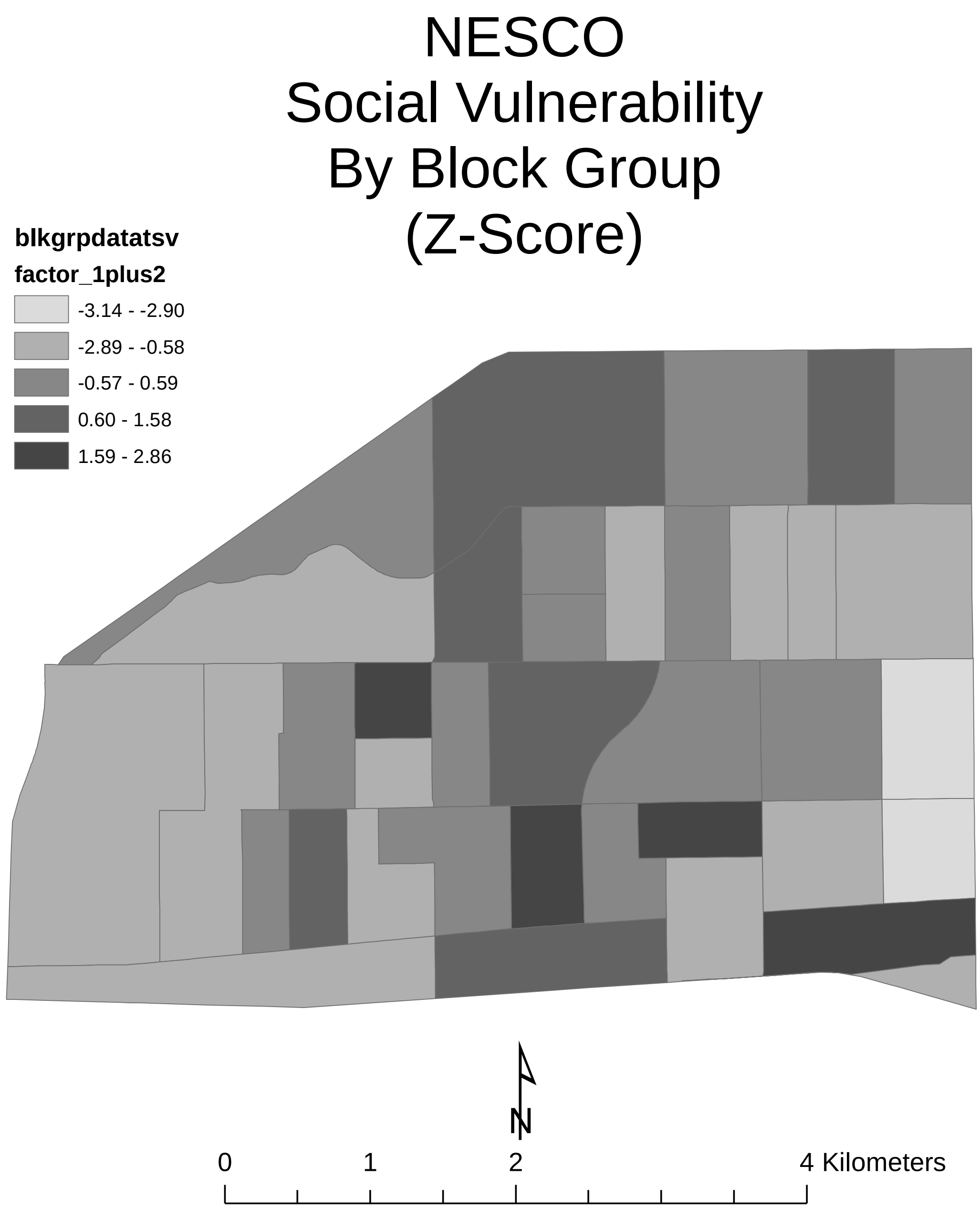

Figure 9: NESCO SV by Block Group

Block Suitability PCA

The variables: average surface temperature, block population count, SV rating, negative canopy percentage, and impervious surface percentage were used in the final PCA to determine the suitability of blocks for tree plantings. The PCA results were similar to the SV PCA since the two components were also above Eigenvalue of one (see Figure 10). The resulting components together explained 59.194 percent of the variance (see Table 6). The first component showed high correlation between the environmental variables negative canopy percent, impervious surface percent, and average surface temperature (See Table 5). The second component showed high correlation between the social variables SV rating and block population count. The final map shows the 52 most suitable blocks for tree plantings which all have z scores of 2.0 or greater (see Figure 11). The z score 2.0, or two standard deviations above the mean, was chosen because they represent the top 7.75 percent of all blocks in the study area. This figure could be adjusted up or down to meet the tree planting budget.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.662
	Approx. Chi-Square	392.670
Bartlett's Test of Sphericity	df	10
	Sig.	.000

Table 4: Block Suitability PCA KMO and Bartlett's Test

Component Matrix[a]

	Component	
	1	2
ZAve_GRIDCODE	.791	.002
negcanopyz	.788	.148
Zimperv_perct	.753	.286
factor_1plus2	-.253	.713
ZPOP10	-.240	.642

Extraction Method: Principal Component Analysis.[a]

a. 2 components extracted.

Table 5: Block Suitability PCA Component Matrix

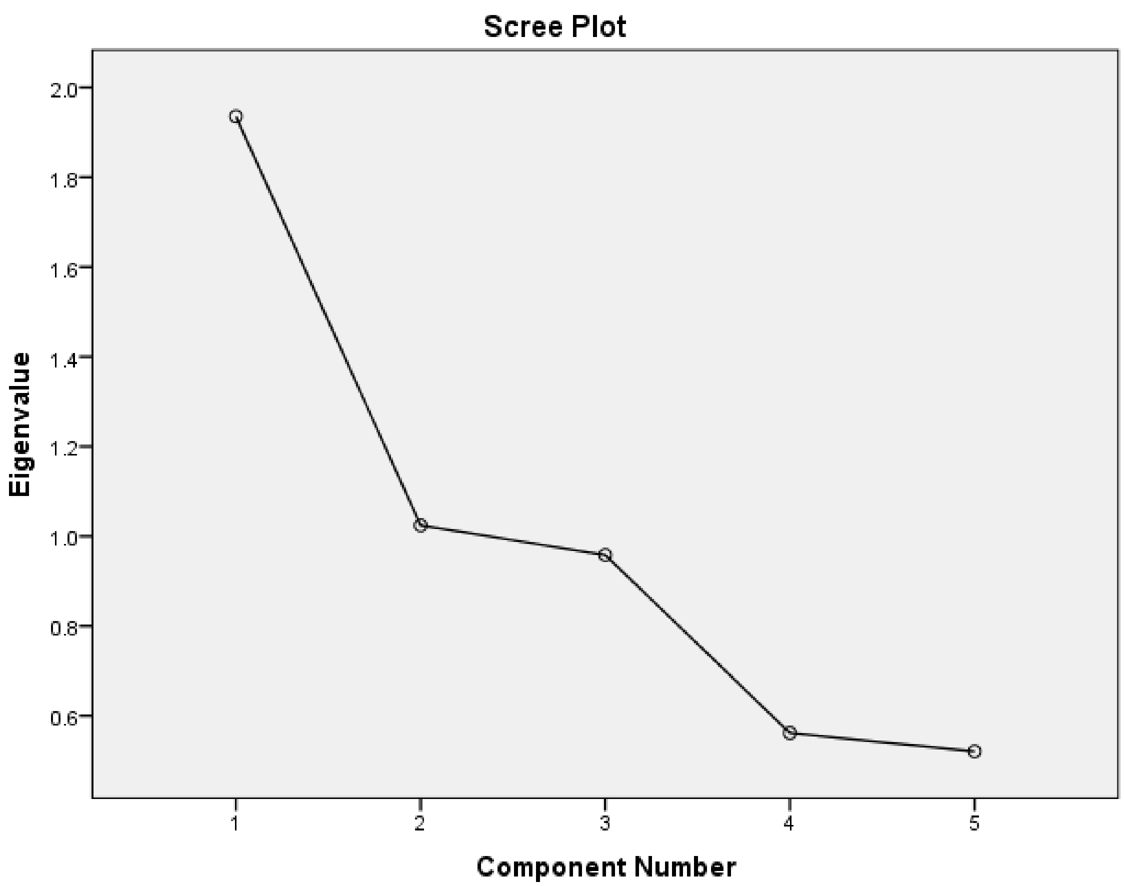

Figure 10: Block Suitability PCA Scree Plot

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.935	38.708	38.708	1.935	38.708	38.708
2	1.024	20.486	59.194	1.024	20.486	59.194
3	.958	19.164	78.357			
4	.562	11.232	89.590			
5	.521	10.410	100.000			

Table 6: Block Suitability PCA Total Variance Explained

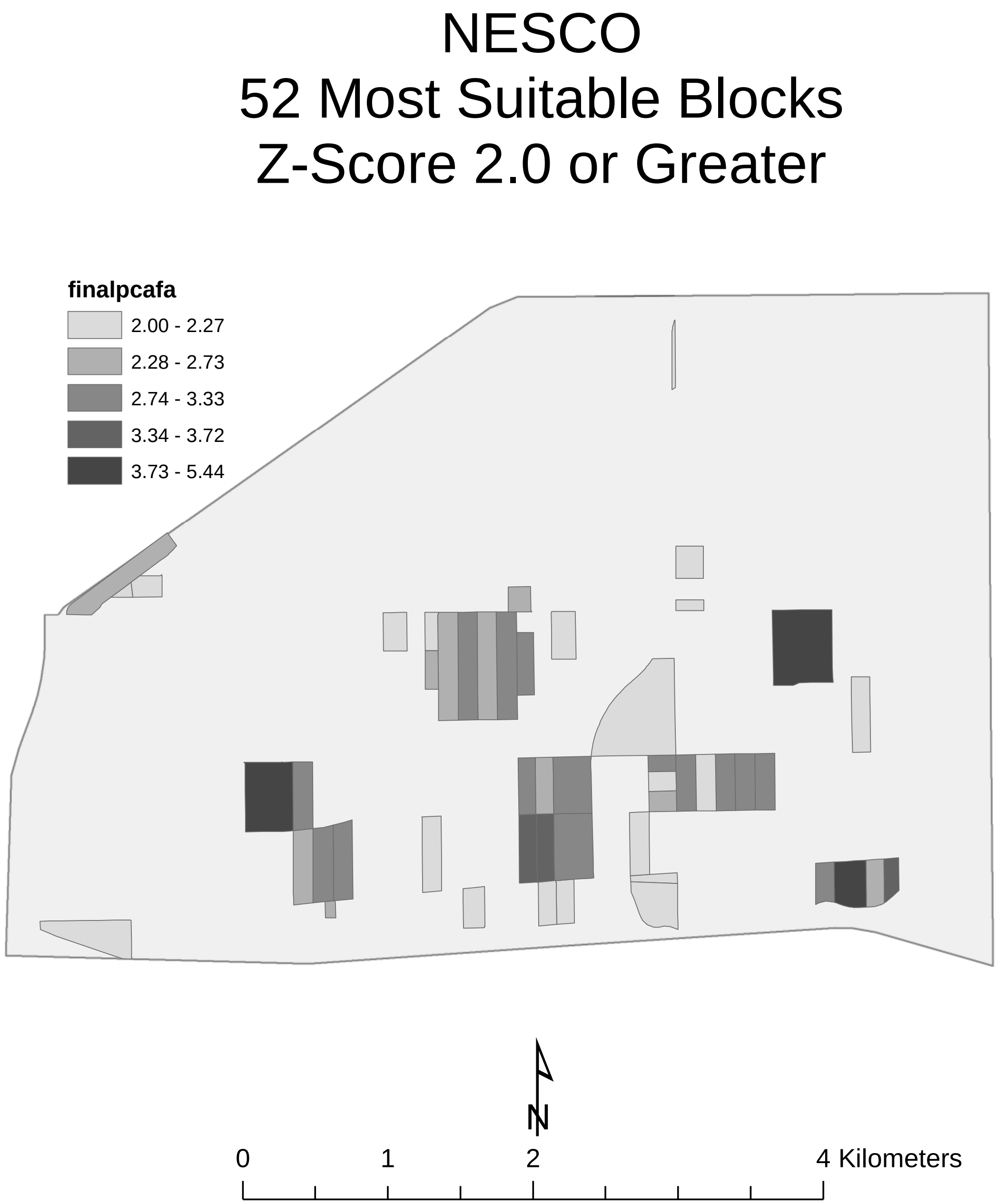

Figure 11: NESCO 52 Most Suitable Blocks for Tree Planting

Plantable Space Assessment

The plantable space within the 52 most suitable blocks for tree planting has been displayed in a NESCO map (see Figure 13). A detailed map of a selection of blocks has been shown with plantable space, imagery, and building polygons (see Figure 14). This product is an example of what an arborist could use to select prime locations to plant trees. Another map (see Figures 15 and 16) was created by using Susan Jones' downloadable ArcMap tool from: http://arcscripts.esri.com/details.asp?dbid= 16089. This tool assists in making pie wedge shaped buffer areas in ArcMap. The pie wedge shapes were based on a centroid point of each building polygon in the 52 blocks. The first angle was at 135 degrees or southeast, and the second angle was at 270 degrees due west. The radii distance was 16 meters, just over 50 feet. As the radii length increased the distance from the building increased. As trees are planted farther from target buildings, it will take longer for the tree to grow tall enough to shade the building. Also, the trees will shade the building for fewer hours of the day and likely not at peak sun hours. By using this tool, high priority plantable space can be distinguished from low priority plantable space.

One type of data that may be useful is parcel data which has the "use code" for every building in the study area. Of the many use codes in the parcel data, single family residence, double family residence, and multi-family residence seems to be the most relevant because these codes indicate that people may be living in the building. To be able to differentiate between these "residential" parcels and other use parcels could be useful for people/organizations planting trees; for example, if they were going to mail out questionnaires to residents in order to determine locations of SV residents. However, it was not needed in this study.

NESCO
Plantable Space

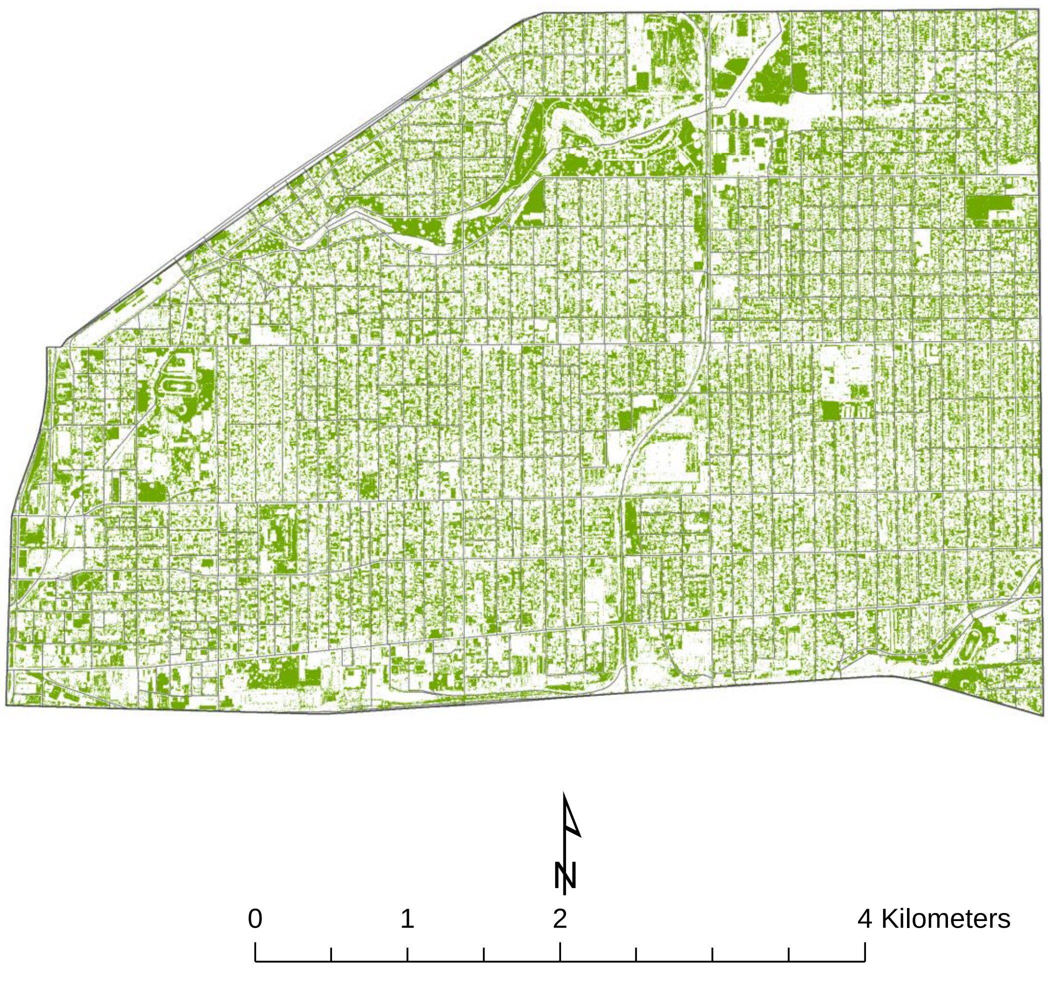

Figure 12: NESCO LiDAR Classification of Plantable Space

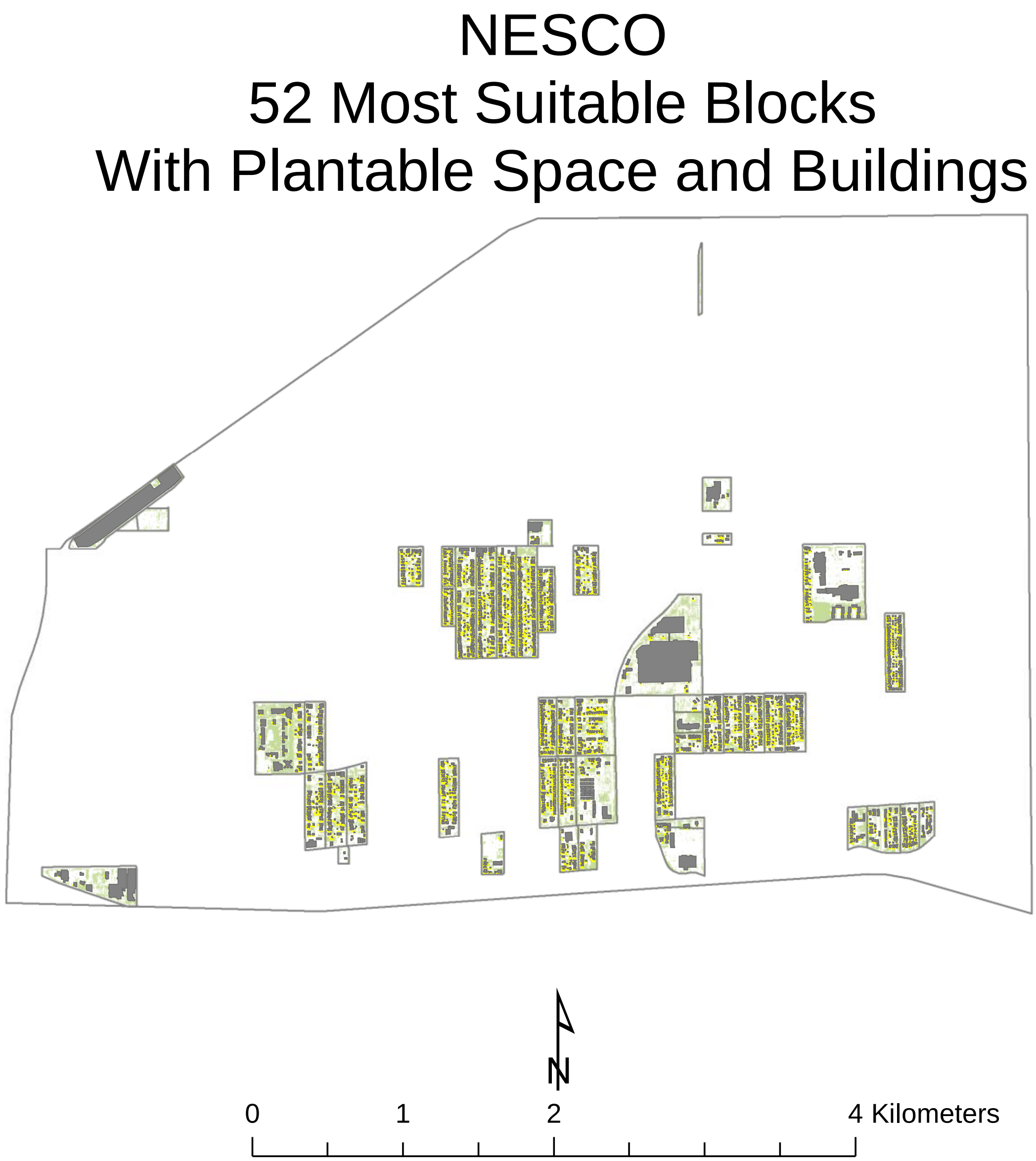

Figure 13: NESCO 52 Most Suitable Blocks with Plantable Space

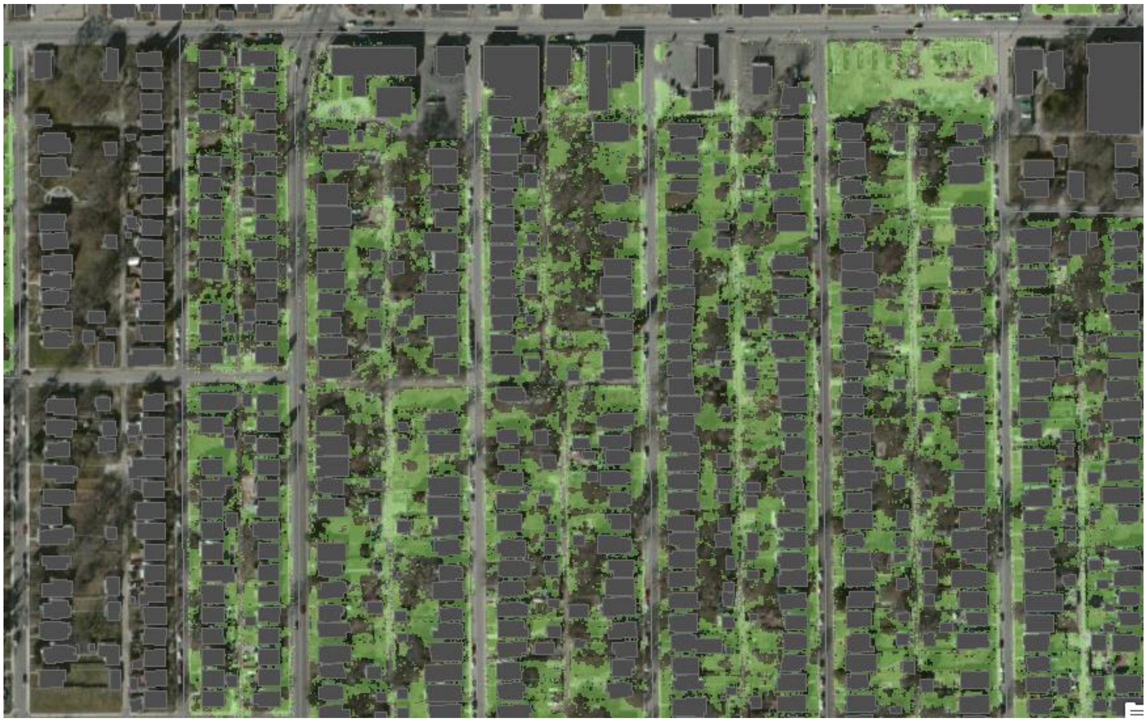

Figure 14: Detail of Plantable Space with Building Polygons and Background Imagery

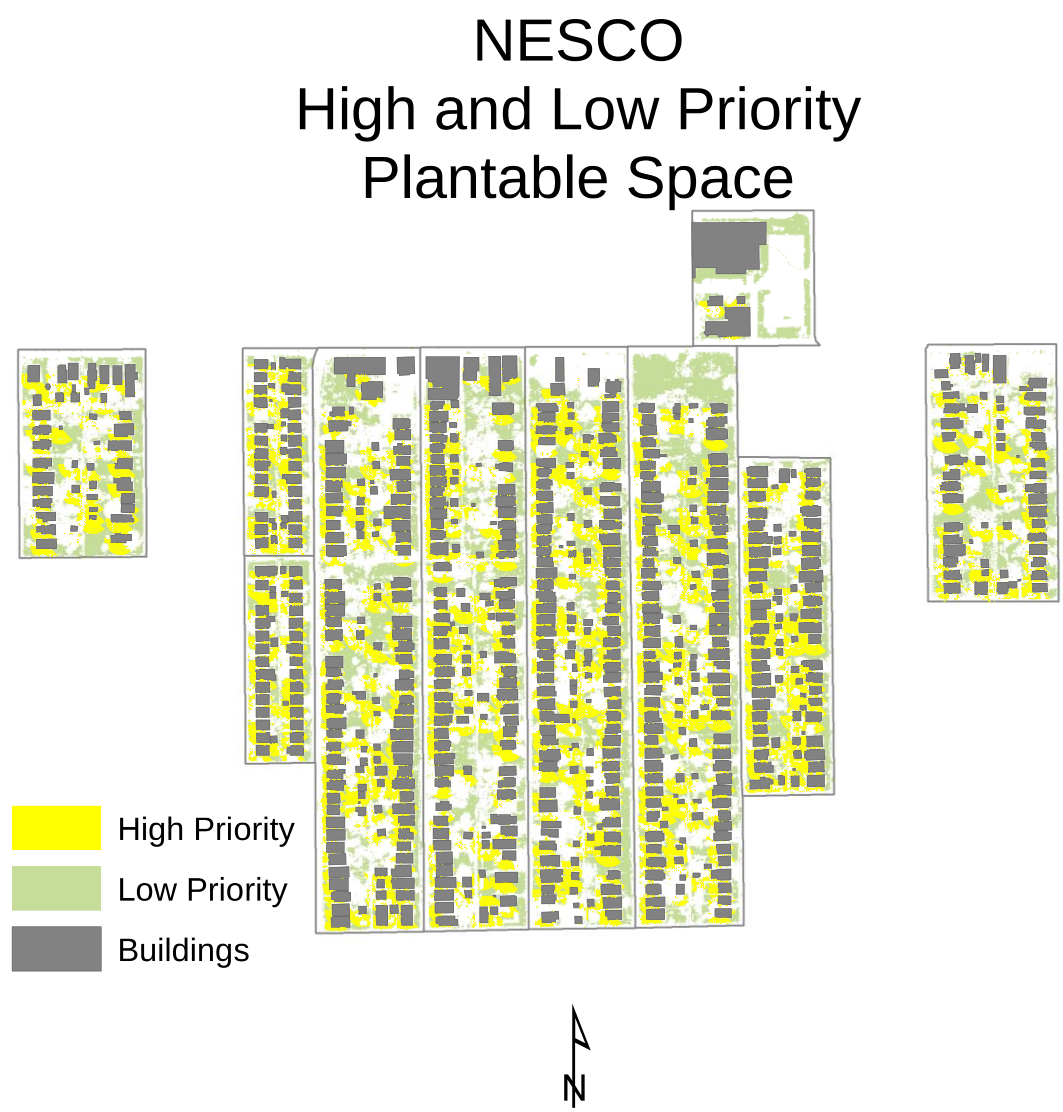

Figure 15: High and Low Priority Plantable Space with Building Polygons

NESCO
High and Low Priority
Plantable Space in Detail
With Pie Shaped Buffers

Figure 16: Detail of High and Low Priority Plantable Space with Pie Wedge Shaped Buffers and Building Polygon

DISCUSSION

LiDAR Classification

The use of LiDAR data is a significant improvement over other available imagery. Landsat satellite images have a much lower resolution, and NAIP aerial photographs have approximately twenty percent of the image obscured by shadows. The one area of the LiDAR classification that needs improvement is the differentiation of bare earth. The technique that was used in this study tended to class bare earth into the impervious surface category instead of the more appropriate plantable space class. The reason this miscalculation occurred was that grass and bare earth have much different intensity values in the ArcMap LAS dataset analysis. A technique is needed that isolates the bare earth from impervious surface. Bare earth consists of less than five percent of land surface in Center Township. The majority of bare earth consists of construction sites and baseball diamonds which are technically plantable but not locations that would be chosen for tree planting in this study. The one type of bare earth that would be useful, if classed with plantable space, is the bare patches where grass has died and the earth is exposed.

Surface Temperature

The results of the surface temperature model correlate as expected. Areas with high canopy percentage have lower surface temperature, and areas with high impervious surface percentage have high surface temperature. The range of temperatures was not as wide as what Rigg (2012) found in her study of all of Center Township, but that could be a result of using a different source image and modeling technique.

Social Vulnerability PCA

The block group SV PCA resulted in two components with Eigenvalues greater than one (see Figure 8). Component one accounted for 41.942 percent of the variance (see Table 1). The component matrix indicated that component one had high inverse correlation between median income and percent population below poverty level (-0.850 to 0.832) (see Table 3). As income decreased the population below poverty level increased. The correlation between the two other variables, population age 25 and above without high school diploma and population age five and below, was not as strong (0.602 and 0.535 respectively) but still indicative of SV populations.

Component two represented 20.452 percent of the variance and was solely the effect of the variable "population age 65 and greater." "Population 65 and greater" achieved a score of 0.951 on the component matrix with no other variable being positive or greater than 0.271. The individual component block group scores were added together to give a SV total z score. The Kaiser-Mayer-Olkin (KMO) test only achieved a score of 0.556 (see Table 2). Ideally this score should be 0.600 or greater for the results to be considered significant since this result could indicate that a PCA may not be the most appropriate way to analyze this data set (StatSoft, 2011). This score could also be a result of having already reduced the set of variables down to five, instead of using a much larger group of demographic variables.

Block Suitability PCA

The block suitability PCA used the z scores of the variables: impervious surface percent, negative canopy percent, block population count, surface temperature, and SV rating. As in the first PCA, two components were found to be significant with Eigenvalues greater than one (see Figure 10). The first component explained 38.708 percent of the variance (see Table 6). All three environmental variables: negative canopy percent, impervious surface percent, and surface temperature had high scores on the component matrix, 0.788, 0.753, and 0.791 respectively (see Table 5). The second component represented 20.486 of the variance for the block PCA. This component represented the two social variables, SV rating and block population count. SV rating had a score of 0.713 and block population count scored 0.642 (see Table 4).

Table 7 in the Appendix shows the attributes of the 52 most suitable blocks for tree planting. The columns “Fac1” and “Fac2” were the results of component one and two and are the reduction of the data to these two components. These two components were added together to give the “PCA Total” from which the highest 52 (all scores above 2.0) are displayed. This table can be useful in determining why a particular block scored so high. A high Fac1 score would indicate the environmental variables were most important whereas a high Fac2 score would indicate the social or populations characteristics were the cause.

The KMO score for this PCA was above the standard of 0.600 with a score of 0.662, suggesting that using PCA was warranted. However, it could again be argued that conducting a PCA with so few variables may not be the best solution.

Plantable Space Assessment

The results of the plantable space assessment displayed the blocks with z scores greater than 2.0. The 52 resulting blocks represented the blocks most suitable for tree planting within the NESCO study area. The attributes table of the 52 blocks (see Appendix Table 7) shows that these blocks were selected for a variety of reasons. In most instances, individual selected blocks have an outlier score in at least one variable, meaning the block most likely had one overreaching characteristic and average scores in the other variables. Some examples of these characteristics include: having a high impervious surface with a high surface temperature score, or having a high block population score with a high SV rating, or having a low canopy percentage. Blocks vary in size and are about a twentieth the size of a block group which could explain how blocks can be so homogenous, consisting of almost one surface feature (canopy, impervious surface, or plantable space). The data, however, does not support this conclusion. In fact, smaller blocks are less likely to be selected as suitable tree planting locations because the average size of the 52 selected blocks is 35,162.63 square meters, and the average size of all 671 blocks in NESCO is 22,179.41 square meters. This result could indicate that block population count played a more important role because larger blocks would most likely have higher populations, therefore more likely to be selected for tree planting. The mean block population for the 52 selected blocks is 88.38 and for all 671 NESCO blocks 45.62.

The use of the pie wedge shaped buffer tool to distinguish high and low priority plantable space is effective but not perfect. High priority plantable space is a space where a growing tree could eventually shade a building. The tool works well for the small homes that predominate in NESCO, but larger buildings or irregular shaped buildings result in high priority plantable space being excluded and shown as regular low priority plantable space. A tool that based the size of the buffer on the shape and height of the building would be better. The plantable space percentage of the 52 most suitable blocks is indicated in the right column of Table 7.

CONCLUSIONS

This study differed from previous tree planting studies in that the scale was at the block level. Questions emerged: was it useful to conduct a study at this scale, does it come closer to depicting the varying conditions as they exist on the ground? If a tree planting organization actually used this study or a similar tool to help determine where trees are planted, would it lead to a more efficient use of tree planting resources with more SV people positively affected? Possible measures of success could be an increased canopy percentage in areas where SV people live, reduced impervious surface percentage, reduced surface temperature, and reduced EHE mortality. It may take a minimum of ten years for newly planted trees to grow large enough to make measurable differences in these variables. As with most research projects, one should maintain that this is one study looking at one small study area with only limited data and that these findings are only an aging snapshot of these data in this location.

This study used 2011 LiDAR data to depict the study area in a precise way and classified all space as canopy, plantable, or impervious surface. The LiDAR data was an immediate improvement over NAIP imagery that had twenty percent of its area obscured by shadows. Landsat 7 imagery from 2011 was used in the surface temperature model that indicated the locations where the UHIE was most prevalent; these areas positively correlated with the locations of high impervious surfaces.

One of the limitations of this study is in pinpointing the locations of SV people. Even if demographic data were available at the block level, the actual buildings with SV people residing in them would still be unknown. It will be necessary for tree planting organizations to develop a method to gain this last bit of knowledge, if truly focused tree planting is to be a reality. Ideas on ways to solicit this information could include the use of questionnaires sent to residents in high SV blocks, or having social workers who are in contact with SV people act as a conduit to the tree planting program. The SV PCA did identify block groups with varying levels of SV. The PCA may have been more statistically significant if more variables were used in the process, but the variables used were those that are most often found to be significant when conducting an SV analysis (Cutter, 2003 and Rigg, 2012).

The final block level PCA found the blocks most suitable for tree planting, given these variables. The fifty two blocks with z scores greater than 2.0 were selected for plantable space analysis. This analysis could be a useful tool for an arborist to use in order to conduct focused tree plantings to help SV populations, reduce the UHIE, and increase the urban NESCO tree canopy.

Further Research

Possible future research stemming from this project includes:

- Refinement of a LiDAR classification technique to determine "bare earth" or use of a hybrid classification between LiDAR data and other imagery to increase overall classification accuracy.

- Development of a better pie-wedged buffer tool to create buffers that are based on the size, shape and height of the building polygon.

- Using historical imagery to measure the environmental changes to areas were tree planting programs have been implemented in the past. Does canopy increase? Is the tree planting program more or less effective in certain areas? How long does it take for tree planting programs to see gains in canopy, reduction in surface temperature and UHI?

- Measure the ability of tree canopy to cover roads as they mature, are certain species better suited than others at thriving in the street environment and spreading over roads and shading other impervious surfaces as they mature?

APPENDIX

LiDAR Classification Results

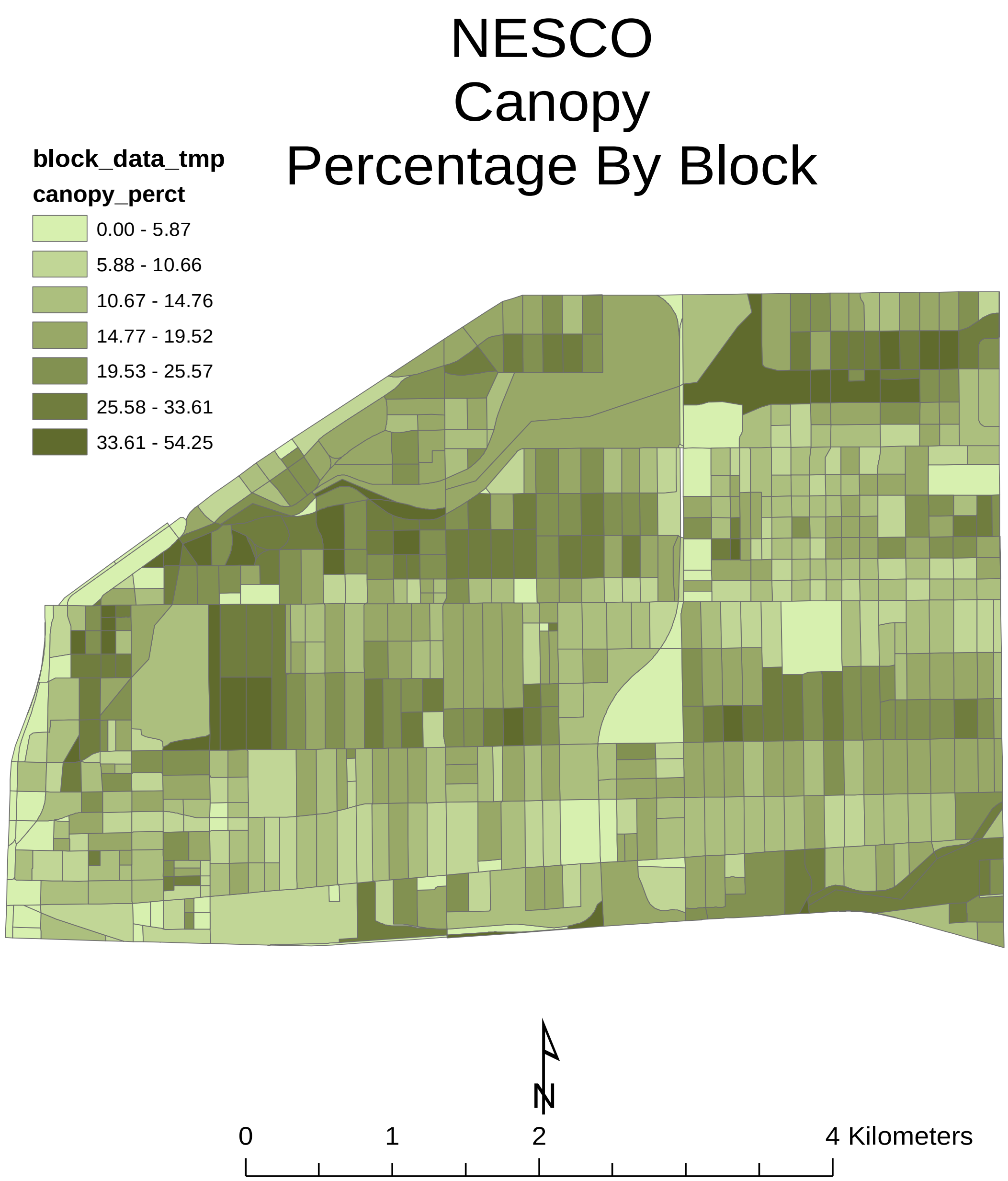

Figure 17: NESCO Canopy Percentage by Block

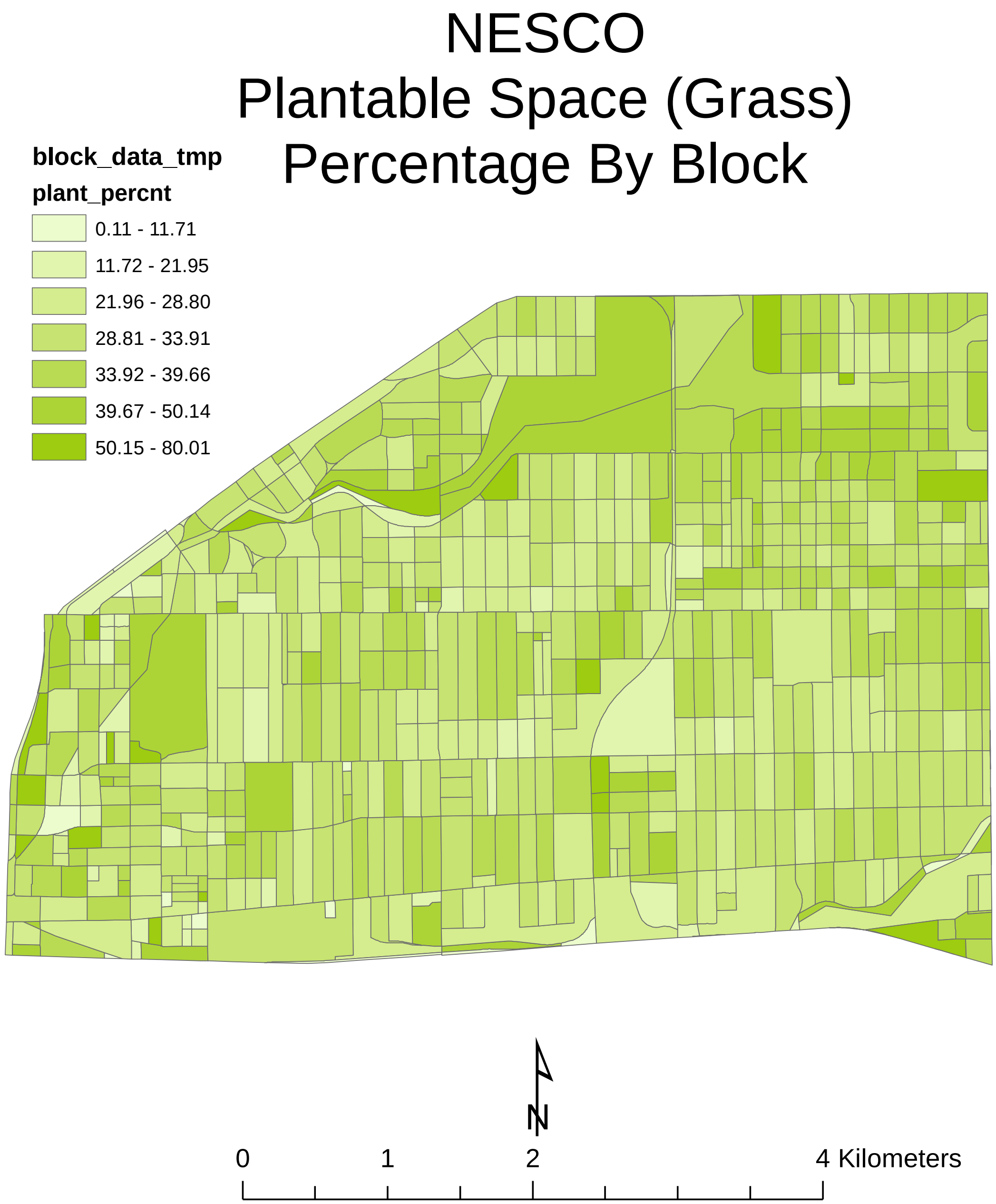

Figure 18: NESCO Plantable Space Percentage by Block

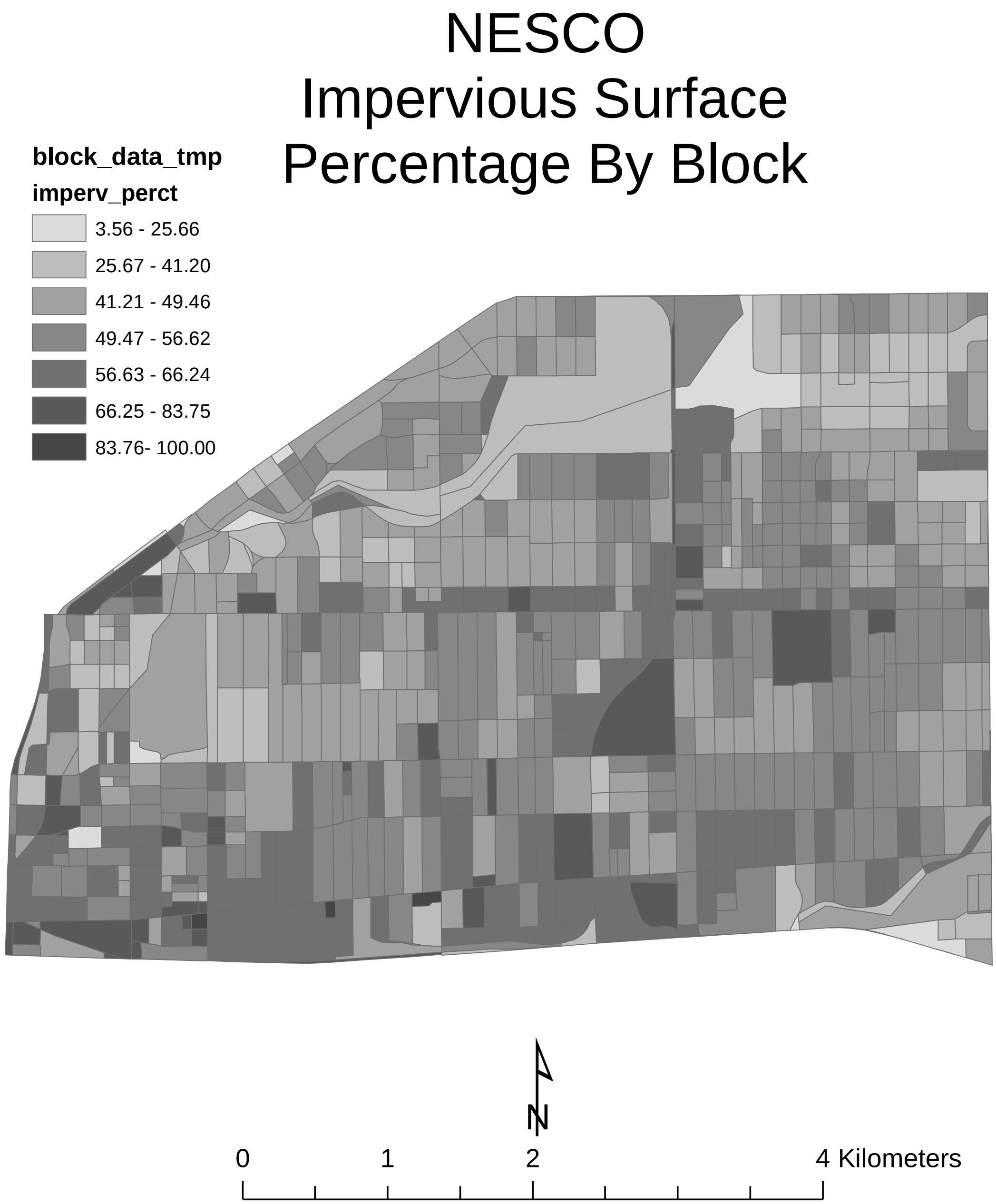

Figure 19: NESCO Impervious Surface Percentage by Block

Figure 20: NESCO Population 5 and Under

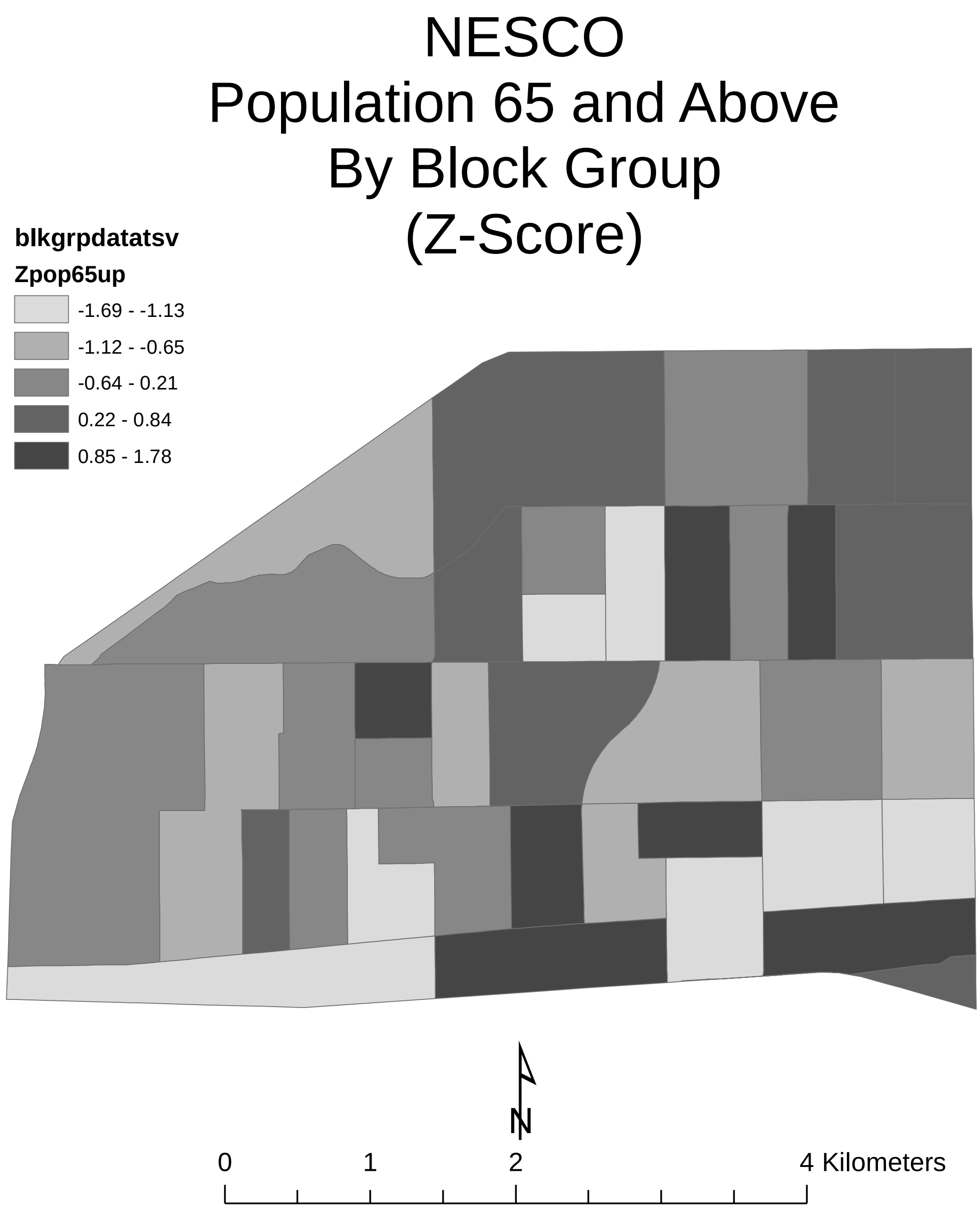

Figure 21: NESCO Population 65 and Above

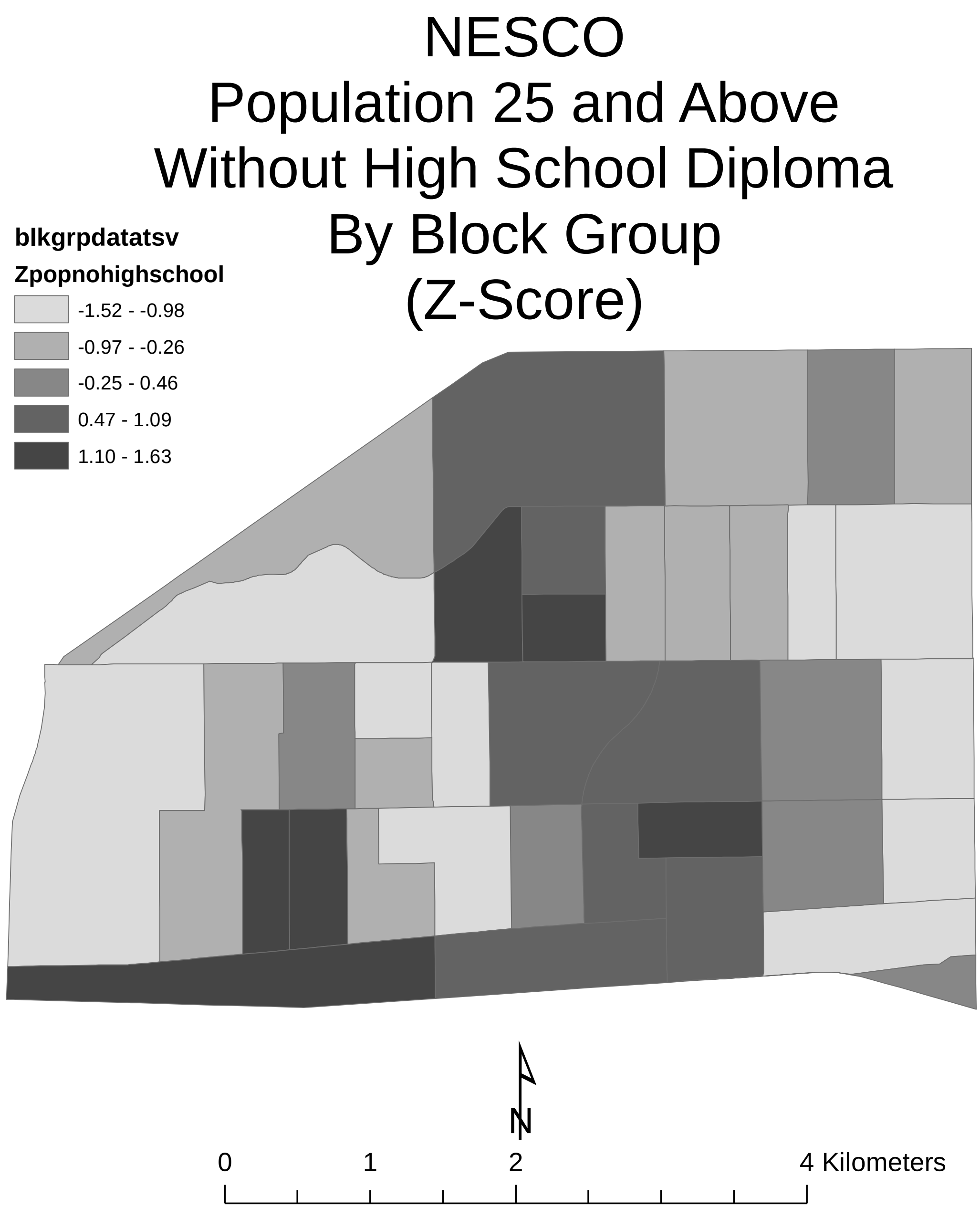

Figure 22: NESCO Population 25 and Above without High School Diploma

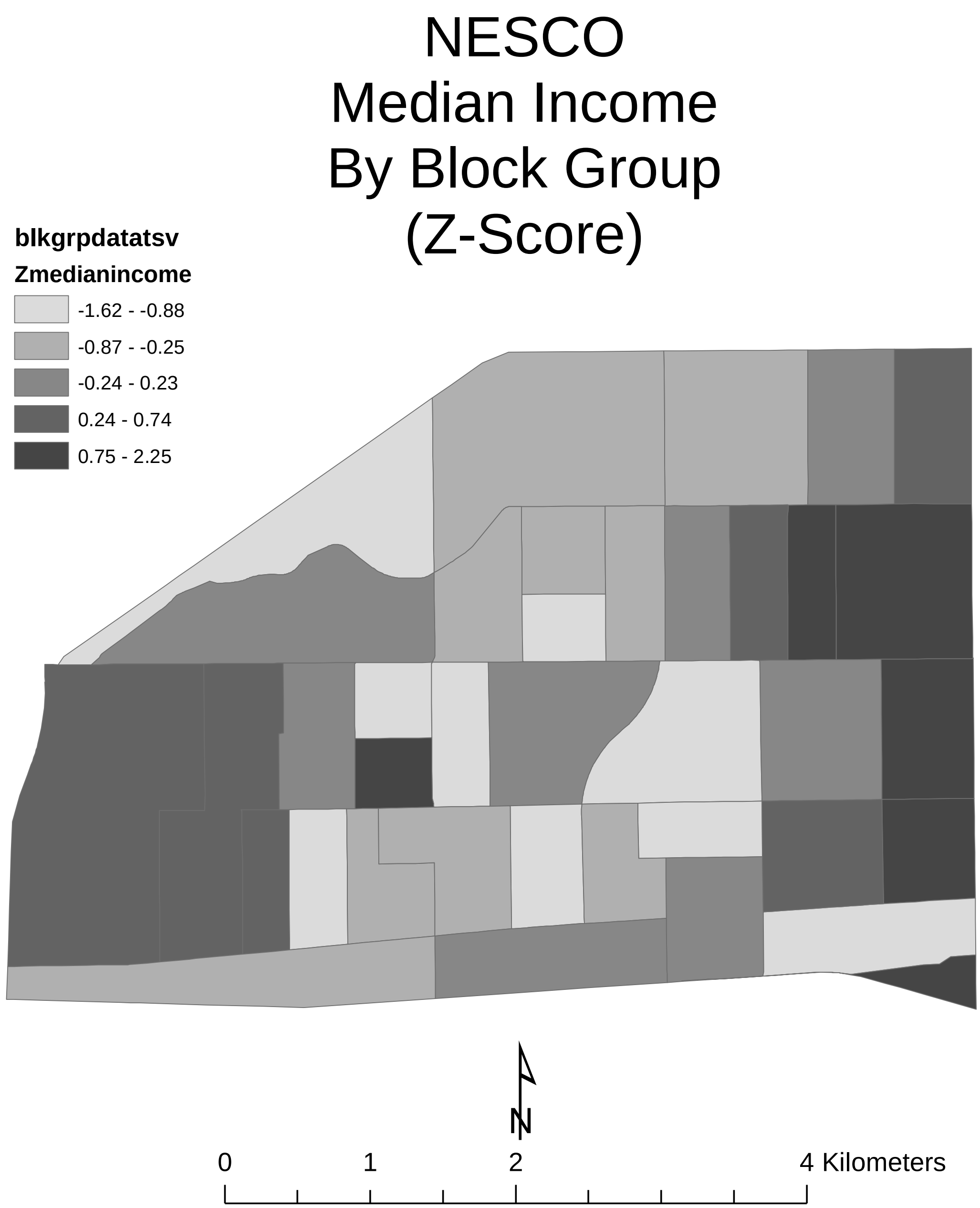

Figure 23: NESCO Median Income

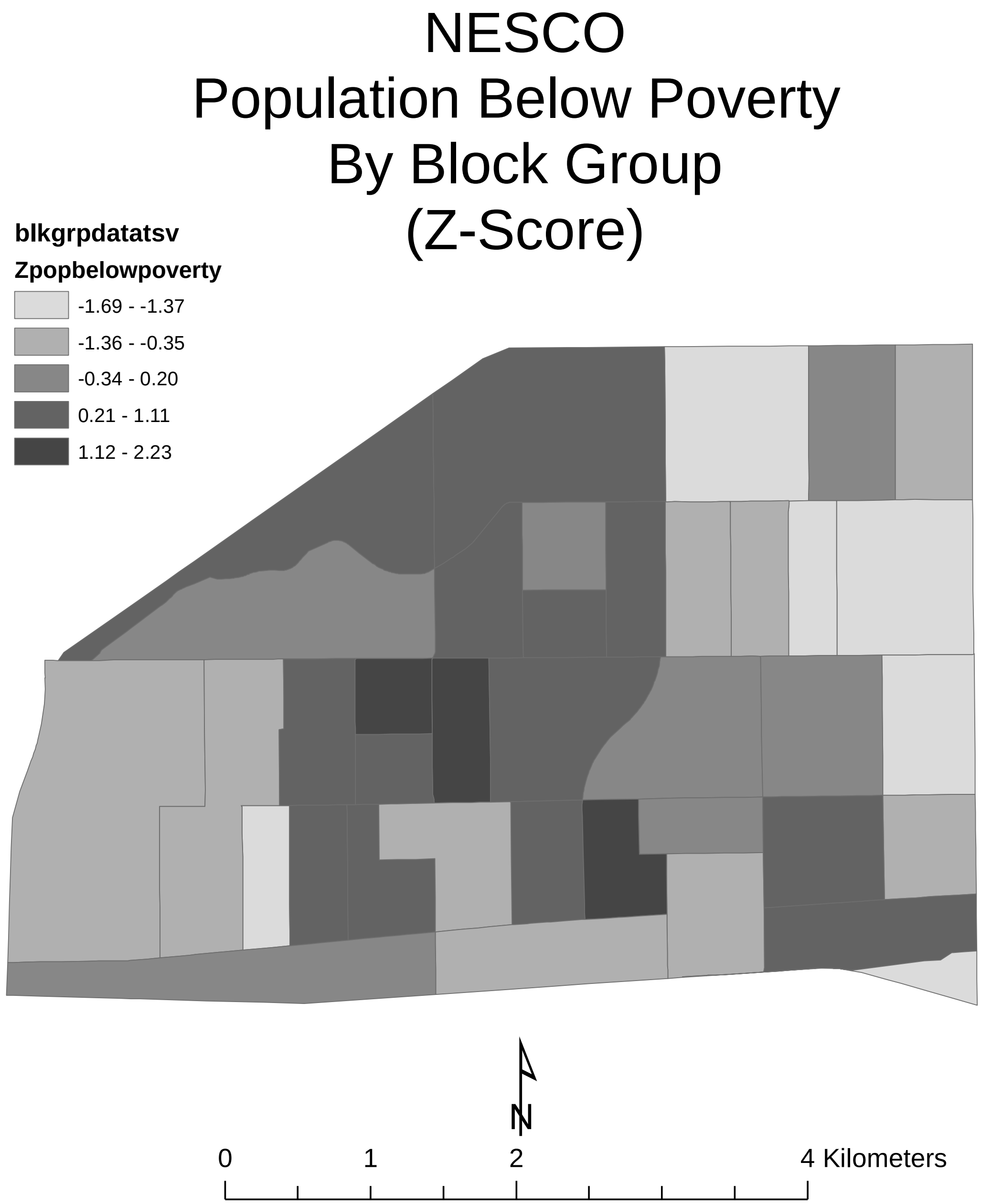

Figure 24: NESCO Population Below Poverty

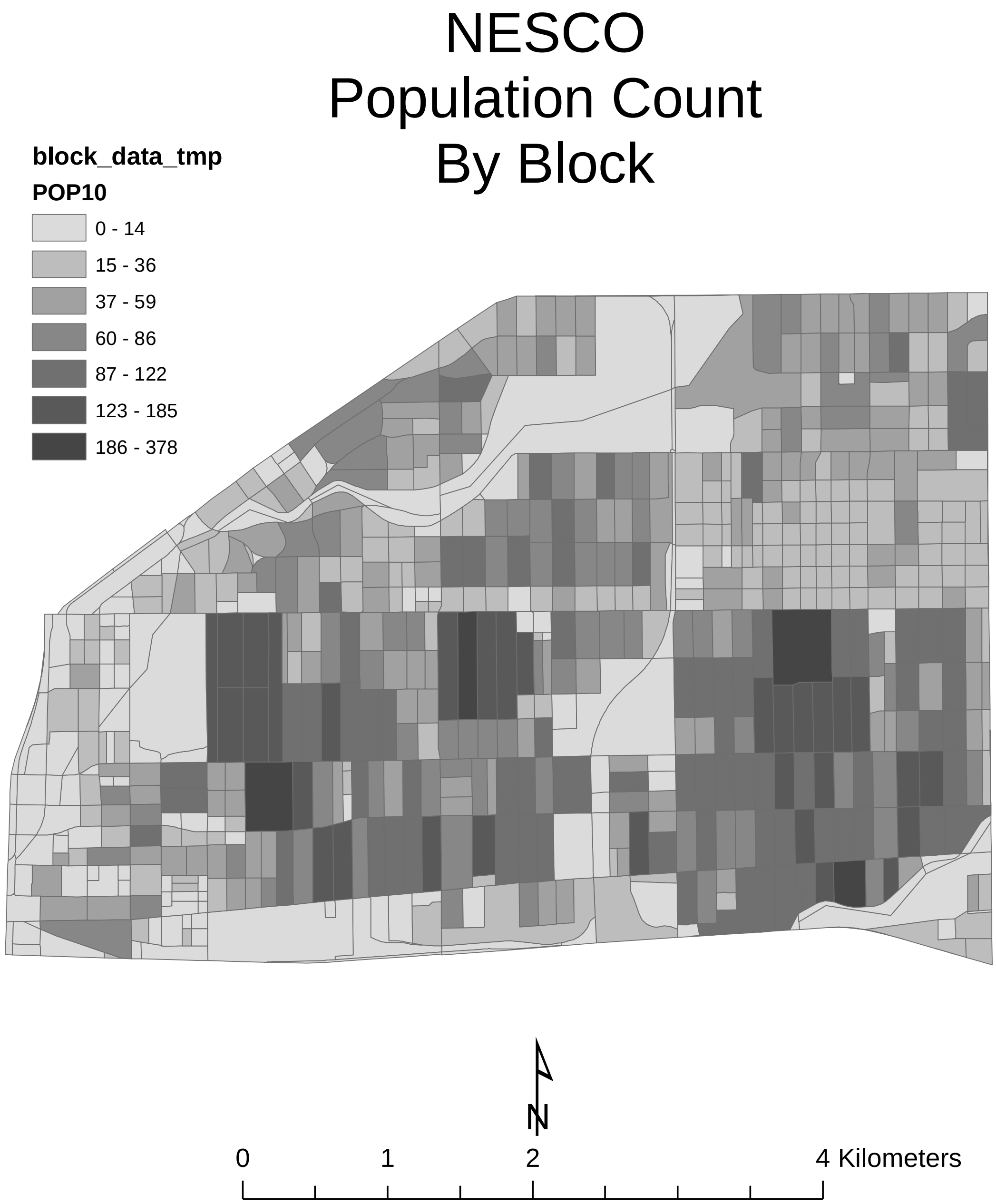

Figure 25: NESCO Block Population Count

Attribute Table of 52 Most Suitable Blocks

OBJID	GEOID	BlkArea	BlkPop	FAC1	FAC2	PCATotal	Plantable%
1	180973545001000	89246	378	0.343	5.103	5.446	48.58
2	180973554002007	38526	214	0.733	4.078	4.811	32.68
3	180973553002003	117931	225	1.945	2.845	4.790	28.57
4	180973554002013	14985	140	0.618	3.120	3.738	23.41
5	180973550001004	31044	101	1.218	2.489	3.707	34.39
6	180973550001003	32682	108	1.071	2.630	3.701	32.43
7	180973526002032	946	2	2.408	1.050	3.458	2.91
8	180973547002007	39914	135	1.069	2.278	3.347	33.93
9	180973548001001	56350	227	0.393	2.928	3.321	31.11
10	180973551001001	30179	106	0.624	2.636	3.260	33.73
11	180973550001002	25945	99	0.774	2.452	3.227	33.04
12	180973554002008	19650	146	0.247	2.946	3.193	36.04
13	180973551001004	30321	109	0.422	2.728	3.150	25.70
14	180973549002015	28691	139	0.872	2.269	3.141	34.27
15	180973551001000	30149	96	0.617	2.520	3.137	28.47
16	180973547002006	41152	132	0.903	2.208	3.111	32.65
17	180973549002016	58182	179	0.381	2.712	3.093	37.09
18	180973551001002	29769	107	0.295	2.742	3.037	31.63
19	180973550001000	57922	120	0.295	2.730	3.024	37.26
20	180973550001005	68541	4	1.716	1.200	2.915	26.21
21	180973547002004	35800	130	0.510	2.374	2.884	24.03
22	180973551001005	12183	0	1.670	1.146	2.816	25.32
23	180973527001056	60911	7	2.932	-0.184	2.748	13.83
24	180973547002005	39251	81	1.027	1.628	2.655	25.77
25	180973550001001	27156	84	0.367	2.160	2.527	31.04
26	180973548001002	57988	163	0.504	1.992	2.496	31.90
27	180973526004011	15180	0	1.986	0.439	2.425	24.11
28	180973551001007	15027	59	0.475	1.949	2.424	32.82
29	180973548001000	56022	167	0.399	2.013	2.412	34.49
30	180973557002006	4576	0	3.078	-0.708	2.370	9.09
31	180973554002006	22830	73	0.406	1.953	2.359	26.67
32	180973548003007	13385	43	0.538	1.812	2.351	32.17
33	180973550002006	38227	153	1.005	1.275	2.280	34.02
34	180973551003005	32828	162	0.317	1.962	2.279	37.22
35	180973548003000	13364	34	0.554	1.705	2.259	28.54
36	180973551001003	29787	87	-0.209	2.457	2.247	30.79
37	180973556001005	21387	55	1.215	1.029	2.243	24.14
38	180973553002006	37086	180	0.242	1.999	2.241	25.22

39	180973527002047	4366	0	2.967	-0.729	2.237	8.88
40	180973525001016	23938	5	1.940	0.290	2.230	16.40
41	180973556001004	23226	13	1.577	0.627	2.204	22.84
42	180973527002043	16508	20	2.509	-0.305	2.204	13.57
43	180973548003002	24320	83	-0.167	2.353	2.186	35.11
44	180973557002012	62440	69	2.235	-0.051	2.184	23.39
45	180973549001006	158960	0	2.691	-0.517	2.174	21.56
46	180973556001000	10887	21	1.510	0.657	2.167	34.39
47	180973525001021	8050	8	1.862	0.301	2.163	18.94
48	180973526002034	5557	0	1.352	0.786	2.137	25.29
49	180973549002004	31007	94	0.567	1.556	2.123	31.45
50	180973551001006	14547	0	1.152	0.927	2.079	42.43
51	180973556001001	48337	0	1.560	0.512	2.073	16.92
52	180973556001007	21176	38	1.146	0.854	2.000	31.77

Table 7: Attribute Table of 52 Most Suitable Blocks

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